Towards a Situation Awareness for eHealth in Ageing Society

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Abstract

Situation awareness is a renowned approach leading to a decision. The results obtained by measuring the awareness of stakeholders in healthcare can provide valuable inputs on the decision-making process. In the world of an ageing society, artificial intelligence in eHealth plays an essential role in the decision-making process of the users and their behaviors. In particular, clinical pathways, as evidence-based patient-care algorithms, describe the process of care for specific medical conditions within a localized setting. In clinical practice, patient-care journeys are generally subject to the recommended treatment interventions which are regulated in clinical pathways. However, unexpected scenarios occur in patient-care journeys and have a dramatic impact on health service delivery of clinical pathways, often when patients are discharged from the hospital and continue to be followed at home. In order to be able to quickly adapt to arising problems or deviations during the execution of clinical pathways, it is very important to be able to monitor clinical pathways in a near real-time manner so as to obtain a current overview of patient care. For this reason, telemedicine, along with the medical and wearable devices, that can now be employed to gather large amounts of data and perform data modeling through artificial intelligence techniques, may improve the clinical pathway management and reduce costs. Therefore, in this paper we introduce a novel Edge Computing framework that encompasses the different applications of telemedicine, ranging from the modeling and adherence to the clinical pathway to the early discovery of clinical deterioration conditions, allowing diagnosis and/or remote treatment through a set of artificial intelligence tools, also assessing the security and privacy issues that may occur during the health data transmission process, thus yielding a situation awareness for eHealth.

Keywords

Situation Awareness, eHealth, Clinical Pathway, Ambient Assisted Living, Internet of Medical Things, Edge Computing, Process Mining, Adversarial Machine Learning, Robotics

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1. Introduction

Situation Awareness (SA), often referred also as Situational Awareness, is a disruptive trend, re-emerging from the US military field, devoted to maintaining an understanding of what's going on around you at every moment and using that information to mitigate risk. This approach is gaining traction in the eHealth sector [1, 2], as clinicians, IT industries, and AI researchers begin to understand the important link between awareness and clinical decision-making.

One of the objectives of SA in eHealth is to customize the therapeutic path, commonly known as Clinical Pathway [3, 4], for each patient including not only the biological characteristics of her pathology, but also the aspects of her clinical history, her characteristic elements, and the environment in which she lives. In this scenario, Telemedicine–a particular sub-field of eHealth–becomes crucial, allowing remote monitoring of the patient at home.

Considering the generic patient's Clinical Pathway as a process model, two main phases happen distinctly: (i) a *supervised monitoring* of some activities, or sub-processes, that are managed by the health personnel of health structures; and (ii) some other activities can be managed autonomously by the patient, in a sort of medical-*unsupervised* manner. Thus, we envision that the latter phase can be processed by an intelligent multi-agent system whose architecture is able to deal with the specific clinical sub-path for the patient at home, also checking that is validated by a doctor or nurse, and guaranteeing its compliance with the actual medical indications specified in the clinical path.

This idea would be beneficial not only for patients but also especially for caregivers, as telemonitoring-related activities deal with mitigating challenging problems in the Healthcare sector. In fact, the ratio between medical personnel and population is continuously decreasing, hence also the access to medical treatments is slowing even more. In spite of the benefits given by its applicability, the research related to SA in eHealth, and in particular to Clinical Pathway, offers several lines of research for still unsolved problems. In fact, the Clinical Pathway is complex and multifaceted [5]: it is not just confined at the time of the medical consultation or of the diagnostic examination, but it extends to a series of steps that the patient must take autonomously without the supervision of anyone. Indeed, in case of hospitalization, the Clinical Pathway steps would be managed by a nurse, who takes care of the patient.

In recent years, in the eHealth and Ageing Society community, the theme of Ambient Assisted Living (AAL) has been widely used through "domiciliary hospitalization" which allows to promote the assistance of a patient at home. In this context, Artificial Intelligence (AI) techniques, Internet of Medical Things (IoMT), and mobile technologies can play a fundamental role in supporting patients at home, constantly monitoring vital parameters, evaluating a potential degradation of health conditions, also requesting the intervention of clinical staff in case of emergency. The wide use of medical, environmental and interactive devices with constrained storage and processing capabilities allows us to state that every single device available in a smart home can convey useful information to be aggregated, analyzed and processed.

For this purpose, SA in eHealth can be achieved by exploiting what we call "new 3-*d* paradigm": *d*evices, *d*ata and (predictive) *d*iagnostics. Starting from the devices it is possible to capture all the data that can be processed by AI & Machine Learning (ML) algorithms to create predictive diagnostics that would foster, validate, and adapt to the patient usual activities at home. In this way, patient's activities would be checked and compared to her assigned Clinical Pathway,

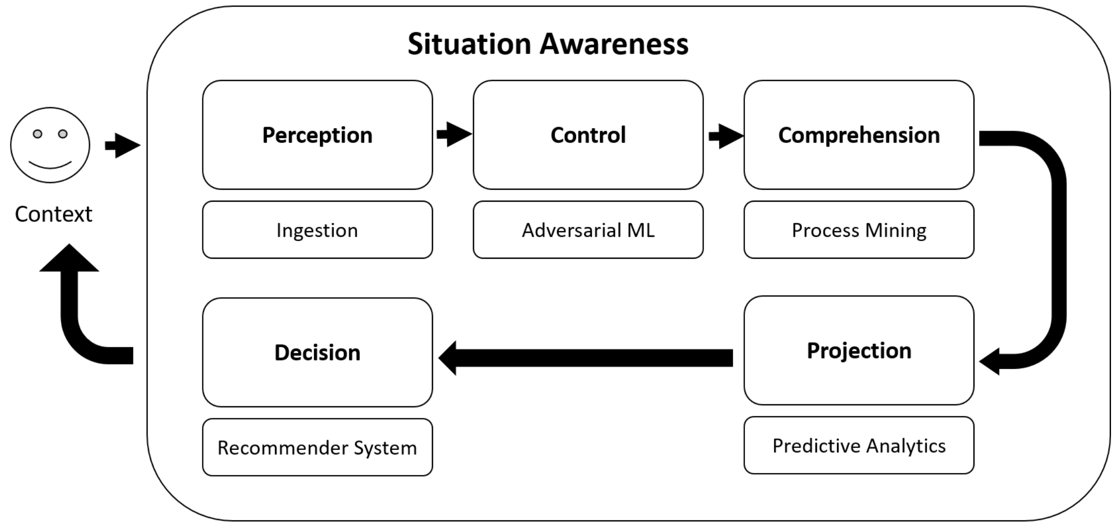

Figure 1: An Overview of technical model of SA in eHealth.

which can be handled as a process model in a Process Mining task evaluation phase, such as the Conformance Checking [6]. When facing this complex task, on the other hand, the security of data must not be neglected. A trustworthy SA system in eHealth and AAL scenario would be able to avoid processing of inconsistent or fake data, which could result in a serious life-threatening for a patient.

Therefore, in this paper, we propose an Edge Computing architecture that, in an AAL fashion, exploits AI models in a multi-strategic approach, to unleash the potential of (medical) end-devices connectivity, supporting thus telemonitoring and telerehabilitation, clinical decision support systems, effective management of health emergencies, the detection of anomaly data or malicious activities related to sensitive vital parameters, and a strict conformance to a Clinical Pathway assigned to a patient at home being remotely monitored. The multiplicity of the various AI techniques, along with the human factor in taking action, would ensure a stronger SA for eHealth in the Ageing Society.

This paper is organized as follows. Section 2 provides an overview of related work and technologies which were investigated as background knowledge. Section 3 defines the Edge process creation and describes the Edge architecture which sinergically leverages on medical end-devices, edge nodes and cloud nodes to perform AI tasks such as Machine Learning and Process Mining. Section 4 describes the possible scenarios of application specifically designed for our approach, such as a cardiovascular failure care pathway and rehabilitation care pathway at home. Finally, Section 5 concludes the paper, outlining future works.

2. Background and Related Work

A desirable condition for giving digital support to strategic decisions during critical situations may be achieved through a SA approach. This is witnessed by the recent health crisis due to the COVID-19 pandemic [7]. Specifically, SA provides a series of techniques and tools to ensure a correct perception, in real time, of what happens in operational scenarios through the precise analysis of information coming from a multitude of heterogeneous sources. As shown in Figure 1, we can see the chain of SA. In the clinical environment, the methods of intervention are always conditioned by the following parameters [8]:

1. *Perception* is related to the data that comes from the context: in this sense, *Data Ingestion*, as first step, collects information from all health information systems and standardize them in a unique formalism.
2. *Control* acts on reliability of perceived data: *Adversarial Machine Learning* is a prominent area of Machine Learning that may help to improve the reliability of systems and protect the ingested data from fraudulent attacks in healthcare where misinformation could endanger and compromise the health of patients [9].
3. *Comprehension* is related to the ability to understand the situation: this is why *Process Mining* for healthcare is an appropriate method to extract information from event logs that are scattered throughout the health system and to define (work-)flows to be analyzed.
4. *Projection* is the ability to prevent future events: for this reason *Predictive Analytics*, by means of Supervised Machine Learning techniques, is a good candidate to predict the flow trend in the system in order to monitor the growth likelihood of critical conditions.
5. *Decision* is the reasoned choice of one of the various possibilities of action or behavior in the face of a situation: *Recommender Systems* may help in personalizing the decision according to previous choices or any similar choices made by others, regardless that the choice is made by a human or an agent.

To achieve greater awareness, it is necessary to monitor the situation rigorously and continuously, through an evaluation process capable of detecting successes and possible bottlenecks of a system. Telemedicine, in this case, allows us to accomplish this task. On the other hand, data are useful only when analyzed. Therefore, AI techniques, previously described at a high level, may help us to perform a SA of the healthcare system, returning an accurate overview.

Process Mining techniques take on particular relevance in eHealth since it is particularly rich of sequential data, even though unexplored. It would become essential to root management by processes in the organization, accompanying the health structure towards the real and in-depth knowledge of its operating mechanisms, through efficient techniques, with low economic impact, in rapid analysis times and ensuring the objectivity of the result. In general, workflows are used to support processes. To understand what it is, some brief notions are provided:

- A *process* consists of a suitable combination of different tasks performed by agents.
- A *task* is a generic piece of work to be executed.
- An *activity* is the actual execution of a task by an agent.
- A process model (or *workflow*) is a formal specification of how a set of tasks can be composed to result in valid processes. Allowed compositional schemes include sequential, concurrent, conditional, or iterative execution.
- A *case* is a particular execution of activities according to a given workflow.
- *Case traces* are lists of events associated to steps (time points). Events of several traces may be collected and interleaved in logs.

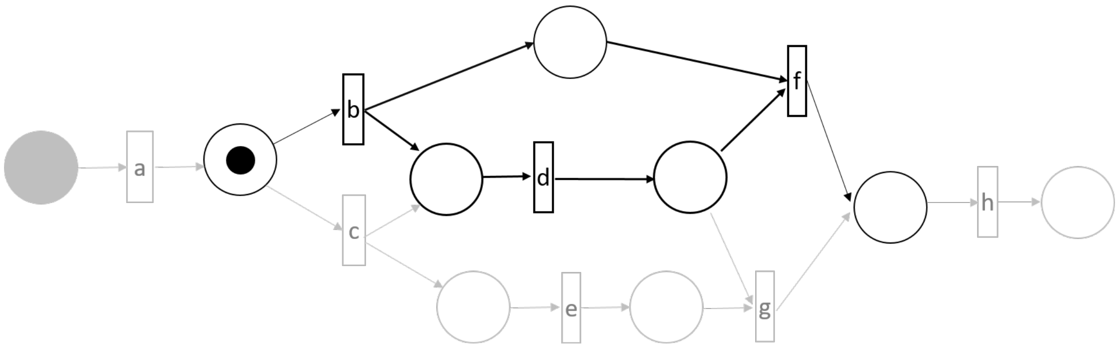

Figure 2: Example of Clinical path depicted by a Petri Net in which circles represent states and boxes represent transitions between activities (i.e., $a, b, c, \ldots$, and so on).

Logs of the healthcare processes can be referred to both the patient and the healthcare facilities, they can be extracted from different sources and they can have different types. For example, the patient's vital parameters, the events associated with him (hospitalizations, rehabilitation, etc.) or, even drug therapy, allow us to define the treatment processes associated with the individual patient. Data from administrative systems, clinical decision support systems, ERPs or medical devices, which can be combined in different views, can be added to this information: from that referring to the patient, to that of the ward, up to the view for the whole structure.

In the clinical field, the term *compliance* describes a patient's conduct, that is, her adherence to prescriptions, defining to which extent a patient's behavior (taking medications, adhering to diets, changes in lifestyle) coincides with the doctor's recommendations. The compliance of the individual clinical procedures represents a problem for the quality of care and the entire health system. For this reason, the *Conformance Checking* technique provided by Process Mining would help us to identify the analogies and discrepancies between modeled behavior (the workflow) and observed behavior (the case traces).

In this respect, AAL systems should exploit contextual information, both to adapt to user needs and to enable tasks independently. In human routines modeling, specifically in the case of Clinical Pathways, it is essential to take into account the flow of the human activities. This is why it is common to use workflows as a routine representation tool. A workflow can be seen as a Petri Net [10], an expressive formalism which can represent activities and their flow, and allows the development of techniques that could handle concurrency. Workflows are used to describe human behavior, showing the succession of activities carried out by the user. In smart contexts or in intelligent environments, this enable to respond to an action with services appropriate to the particular situation. Therefore, having defined the overlap between the workflow and the clinical pathway as the sequence of events that are performed by a patient, this can be assessed with process mining techniques to ensure adherence to the prescriptions of the doctor and compliance with the clinical guidelines. To improve the performance of the system, at this stage, it is necessary to bring the process evaluation component on-board the Edge module.

An example of organizational eHealth processes analysis has been proposed by [11]: the combination of event data and process mining techniques allows them to analyze the operational processes within a hospital based on facts, thus providing a solid basis for managing and improving processes within hospitals. In [12] an ontological model for the audit of the Clinical Pathway is proposed to improve the quality of services and reduce hospital costs. While, a methodology to develop a clinical or dynamic treatment path to facilitate the diagnosis and treatment of patients with Heart Failure, relying on machine learning techniques, is in [13]. Interestingly, the work in [14] is more focused on a well define condition like suffering from aftereffects of a stroke event, however, it does not account for monitoring the patient at home.

A literature review proposing a taxonomy of problems related to clinical pathways and explored the intersection between Information Systems (IS), Operational Research (OR) and industrial engineering is available in [15]. While, in [16] the authors analyze the context-awareness and the adaptivity in executing daily living care pathways in AAL scenarios. The studies conducted in [17, 18] investigated throughout the introduction of Process Mining techniques to analyze, optimize, and improve Clinical Pathways. Authors in [19], instead, provided a formalization of the methodological and technological approach to Clinical Pathway, improving the way patients are monitored.

Due to various challenging issues, such as computational complexity, Edge Computing is a disruptive and promising solution that pushes substantial processing and storage resources from the network core to the network edge, close to mobile devices or sensors. In particular, AI on Edge is emerging as a new paradigm to leverage medical devices and applications, connected to remote (and potentially distributed) Hospital Information System (HIS) through the Internet. Its pervasive diffusion is promoted by the massive usage of smart and wearable devices and Internet of Things (IoT) communication technologies in the healthcare domain.

Authors in [20, 21] shed light on the IoT potentiality in the integration and harmonization of data produced by Cyber-Physical Systems (CPS) with those already present and generated by classical information systems, thus combining people, processes, data, and things. While, works in [22, 23] dealt with a clinical and operational context to develop integrated solutions for seamless care in which AI and IoMT are used at the Edge, with a people-centered approach that adapt to the needs of healthcare providers and that are embedded into their workflows.

Finally, Ardito et al. in [24] present an approach to combine IoT technologies with End-User Development (EUD) paradigms and tools to identify innovative scenarios where end users are directly involved in the creation and customization of the AAL systems they use.

3. System Architecture

In this section, we want to show the applicability of process mining in eHealth, as a mean of AI on Edge model to perform an automatic decision, and proactively support the patient at home. The Clinical Pathway includes numerous steps: some of them are strictly related to an intervention by the health personnel, others need to use medical instruments. From a methodological and formal point of view, the Clinical Pathway process can be represented through the use of a Petri Net, as in Figure 2. Each activity is a node in the Petri Net. These nodes can, in turn, be sub-processes. Using a formal notation, the following definition is proposed.

Definition 1. *The execution of a process σ is described as a sequence of actions $\sigma = \langle a_1, \dots, a_n \rangle$, where $a_1, \dots, a_n$ is the sequence of the single activities carried out by the user in a specific and strict*

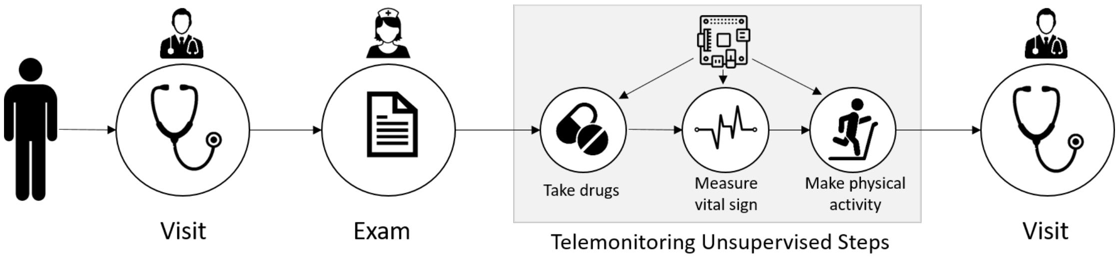

Figure 3: Steps of a Clinical Pathway.

order. We denote with $l_\sigma = n$ *the length of* σ*.*

At the time of the patient's hospital discharge and her return home, the patient's task is to follow the doctor's prescription, in order to preserve or improve the clinical situation. The prescription is transformed into a series of steps that make up the patient's clinical path and must be performed autonomously by the patient. When monitoring takes place at home, we introduce a new layer of supervision to replace the medical staff, as shown in Figure 3.

Patients are equipped with an Edge component that is capable of processing the trend of the patient's behavior on-site in a self-consenting and self-assessing way. The portion of the clinical pathway that needs to be supervised at home can be considered as a subset of actions that the Edge component will have the task of verifying. Formally:

Definition 2. *Given an execution process* σ*, an execution of a sub-process* τ*, managed without supervision, is described as a sequence of actions* $\tau = \langle b_1, \ldots, b_m \rangle$*, with* $l_\tau = m$*,* $\tau \subseteq \sigma$ *and* $l_\tau \leq l_\sigma$*, and where* $b_1, \ldots, b_m$ *is the sequence of single activities, arbitrarily carried out by the user.*

A translation of these steps becomes a prescription to follow that cannot be verified except in the patient's level of rigor. Our idea is to create a level of supervision, based on Edge computing, which can somehow govern the steps of the Clinical Pathway that the patient must follow independently at his home to avoid worsening the clinical picture and bring it to a speedy recovery.

The proposed Edge architecture provides a patient enrollment layer to associate patient types with specific monitoring types (e.g., chronicity). The Edge infrastructure finds the most appropriate Clinical Pathway model by connecting to the cloud and downloading the clinical sub-pathway as a validated sub-process model. The implementation of the monitoring phase involves the elicitation of a series of medical devices that allow the collection of data. These are sent to the Edge module that transforms them into logs in a standard format (e.g., eXtensible Event Stream, XES), compatible with process mining techniques.

The analysis of logs can be performed immediately for each execution of every single step (i.e., measuring pressure, taking a drug, etc.) to verify the compliance with the model. Alternatively, in less severe clinical pathways, it can be carried out at the end of the period (e.g., a day), in order to assess the risk level on single activities or on the entire pathway. In case of non-compliance between the execution instance and the model, the Edge module reports the problem to the medical staff.

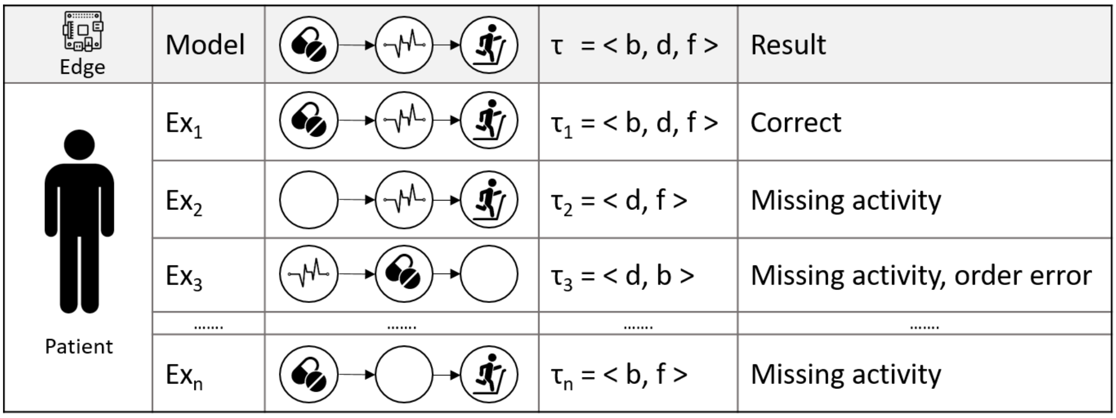

Figure 4: Execution of Clinical Pathway Steps by the patient.

Figure 4 shows the executions of the Clinical Pathway steps performed by the patient. The translation of these actions into a formal notation makes it possible to use algorithms that check conformance and detect deviation from the model. Based on the deviation, it is possible to evaluate the risk (e.g., missing to take a drug) and also to define the corrective actions to bring back the executions towards the correct pathway model. Once the reference model has been defined, the Edge component will be able to verify in real-time (online) the correctness of the operations performed by the patient in the home concerning the clinical pathway.

3.1. CPAD: The Clinical Pathway Security Module

Machine Learning has a fundamental role in the Edge Architecture to predict when a clinical deterioration of vital parameters is about to happen. The monitoring of these parameters is specifically carried out using Supervised Machine Learning methods. In particular, these methods are also used pervasively in AAL scenarios as they can be used to determine whether communication between the devices that are used to monitor the patient under observation is correct or has been compromised. However, these supervised learning methods used in the detection of intrusions in the communication between devices (and the related data exchange between them and the Edge node) have traditionally been developed on the assumption that the environment is benign.

Usually, it is reasonable to presume that there are no opponents trying to circumvent the patient monitoring system. However, it is useful to include a module in the data collection and monitoring system that is capable of detecting anomalies that occur on the system. The system that is proposed in this work is able to monitor several vital parameters of the patient (e.g. arterial pressure, heart rate and respiratory rate). A compromising of the data detected by a sensor worn by the patient would risk compromising the clinical pathway, the doctor's diagnosis, and the patient's own health.

Hence, in order to check if the data transmission is correct, it is proposed to equip with a module called Clinical Path Anomaly Detection (CPAD) [25]. The CPAD module analyzes all the data transmitted from the devices monitoring the patient to the Edge node and eventually notifies detected anomalies. Using specifically machine learning techniques, the module manages the security issues that could occur during the data transmission process. The CPAD module is able to address the security risks that may occur during the data transmission process, through a Cognitive Security approach that uses advanced Artificial Intelligence (AI) techniques. Cognitive AI learns at each interaction to proactively detect and analyze threats that are detected and provides the physician with an explanation of the intrusion. In doing so, by providing the physician with the intrusion detection and explanation, we will be able to correct the patient's clinical path immediately.

From the point of view of technological perspective, the data collected in the node can be seen as a queue and as organized into several sub-processes. Each sub-process represents the detection phase of a vital parameter from a single device worn by the patient. Thanks to the adoption of a recurrent sequential Long Short Term Memory (LSTM) autoencoder, the CPAD analyzes the various sub-processes of the chain to perform the detection of anomalies on the steps of the chain [26] [27]. In fact, the advantage of using sequential LSTM autoencoders is double: first of all exploits the advantage of the dimensionality reduction and extraction capabilities of the autoencoder to efficiently perform the data reconstruction process, and then detect the anomaly and secondly using LSTM networks to manage the sequential nature of the data detected by the sensors.

In this context the anomaly could also consist of an attack to the monitoring of the patient's clinical parameters. The detected anomaly causes a dysfunction in the Clinical Pathway that in turn has a direct impact on the patient's health. The anomaly may represent a direct attack on the vital parameters monitoring phases in order to modify the expected behavior of the detection or to compromise it completely, with relative tampering of the clinical path. Through intrusion detection techniques, the objective is to prevent attacks in the subsequent phases of clinical path management and to provide intelligent information to the physician who gives the treatment, allowing computer experts to isolate the security breach and to reprogram the clinical path together with the physician.

3.2. Edge Computing Cognitive Architecture

In this section we present the proposed Edge Computing architecture that allows the processing to be done at the devices (i.e., end-nodes), or at the gateways (i.e., Edge nodes). This will reduce unnecessary data traffic and processing latency, and it is important for applications such as critical patient monitoring and analysis. In an AAL scenario, we deal with a large number of heterogeneous devices which differ from each other in computational, storage and communication capabilities.

Therefore, the Architecture depicted in Figure 5 presents in the lowest level a Medical and an Ambient Interactive End-Devices Layer:

1. *Medical Devices*: any device intended to be used for medical purposes, such as the diagnosis, prevention, monitoring, treatment, alleviation or compensation of a disease or an injury.
2. *Ambient and Interactive Devices*: any type of mobile or stationary hardware component which enables the interaction between the human being and an application or the environment of the user, characterized by their ability to be perceived at-a-glance, such

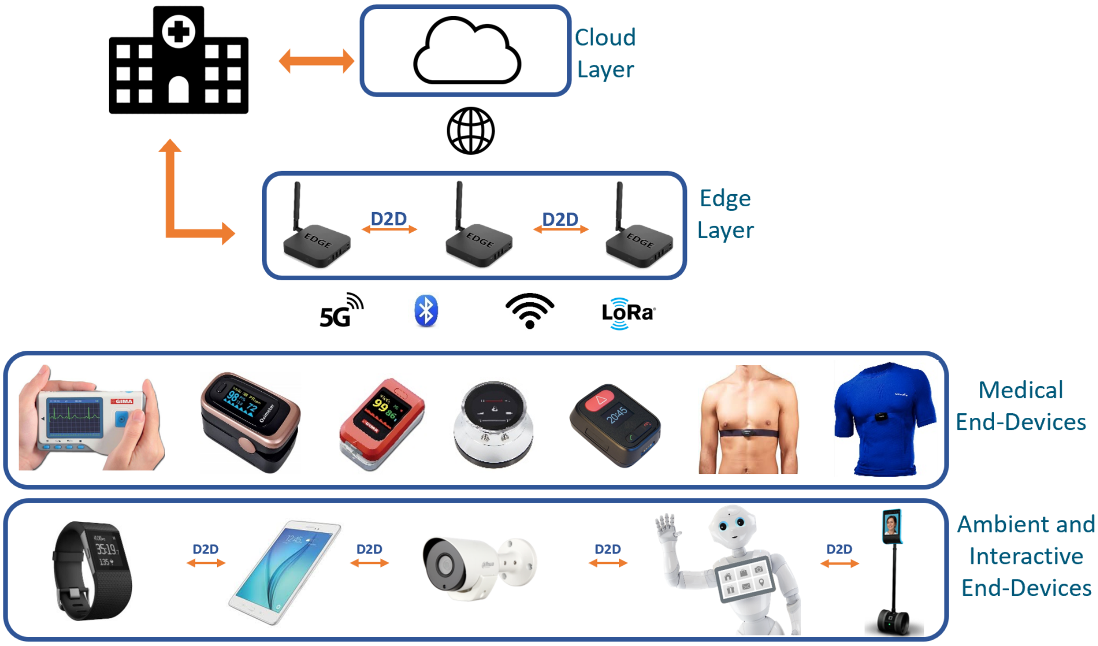

Figure 5: AAL Edge Architecture.

as smartphones, speech recognition devices, wearable devices, motion sensors, cameras, smoke sensors, etc.

At the upper level, there is the Edge Layer made of one or more Edge nodes which can be a nearby end-device connectable by device-to-device (D2D) communications [28], a server connected to an access point (e.g., WiFi, router, base station), a network gateway, or even a micro-datacenter available to nearby devices. We envision that an Edge node can collect useful information from medical, ambient and interactive end-devices, and process them for a particular purpose. In the Edge Layer, a node is designed to execute *Conformance Checking* on a predefined sub-process of the Clinical Pathway, another node may be used as an *Anomaly Detection Module* which is able to address the security risks that may occur during the transmission process for the gathered data (e.g., the CPAD module), and a third node can be adopted as *Adaptive ML Module* for prediction of clinical risk classes of a continuously monitored patient in a particular condition where a limited number of vital parameters is promptly available.

As depicted in Figure 5, the Edge nodes can communicate with each other and exchange the results of a preliminary Edge processing step. Finally, the Architecture presents a Cloud Layer in which gathered raw data and processed data (at the Edge) are conveyed to optimize the overall performances and provide a refinement of the clinical pathway in case of patient's condition degradation. In this way, the Cloud Layer would act as an intermediary, by receiving any request and/or alert sent by the Edge Layer after the measurement of specific vital signs, and by activating specific operating protocol with the hospital or the clinical staff, thus supporting a (remote) complex and adaptive decision making process.

4. Use Case Scenarios

In this section, we present three usage scenarios for clinical pathway handling on Edge. The first one is an IoMT-based scenario, while the other two are based on the use of a Robot.

4.1. Post-Heart Failure Situation Awareness

A heart-failure patient is going to be discharged from the hospital cardiology department after a surgery. He is provided with a kit of medical devices and an Edge module. He lives alone and has difficulties in managing his illness. He should follow an appropriate diet, take the right amount of drugs and adopt an active lifestyle. In particular, the patient receives from the doctor the following advice:

- Body weight should be checked daily if there has been a recent episode of decompensation or if the patient feels less well. If a rapid weight gain is observed (2-3 kg in a few days), it is necessary to notify the doctor. It is useful to have a precise scale and always follow the same rules for weighing: in the morning, on an empty stomach.
- Arterial pressure should be checked frequently. The optimal pressure is between 130/80 and 120/70. However, many patients tend to have it lower. The maximum pressure of 85-90 is not alarming if it is not associated with symptoms such as dizziness and tiredness.

The Edge module downloads the patient's clinical pathway from the cloud and enables the steps that must be activated at patient's home. Based on the types of activities to be performed, the appropriate medical devices are involved, in order to detect and check different vital parameters. For example, activating the pill dispenser to monitor the intake of drugs; activating the pressure meter to verify the patient's clinical status. In this way, the patient feels safer because he is monitored and informed about his illness, possible complications and activities to carry out. The healthcare staff at the medical Control Room, through the monitoring system, receives the monitoring data, checks the progress of the clinical pathway and evaluates any health alterations that could require a change of therapy or a possible re-hospitalization. The patient and his relatives are more relaxed and live the discharge from the hospital more serenely as the Edge infrastructure ensure a high degree of surveillance and proactive collaboration. This is a typical scenario addressed by the project PROSIT[1].

4.2. Domiciliary Hospitalization with Collaborative Robots

In a "domiciliary hospitalization" scenario, an important role can be played by a robot. A robot can be seen as an high interactive device, able to establish a dialogue with the patient in order to capture the cognitive aspects that a standard medical device is unable to detect. With the ability to see through its cameras and through use of specific computer vision algorithms, a robot can understand the environment in which it operates and can understand the context in a particular moment, in order to provide more detailed information for a decision making process. Moreover, the robot's vision can be used to monitor the execution of a patient's activity, such as the correct intake of a medicine or the correct execution of a particular rehabilitation

[1]PROSIT: "Sviluppo, applicazione e validazione di PROdotti, Processi e Servizi per la SanITà Digitale".

exercise. Robots are also equipped with actuators, through which is possible to establish a physical interaction with both patient and with the environment and all the objects present in it. But robots not only can work autonomously, they can also facilitate and make more immediate the remote intervention of a healthcare professional, who is able to interact with the patient through the robot and all the sensors and actuators it is equipped with.

We envision to create a smart home environment in which a robot has a key role. A general description of the workflow for home hospitalization with a robot is shown in Figure 6. The first scenario consists in the monitoring of the patient in his home. The *Medical Devices* measure the vital signs of the person and they send data at the *Edge Layer*, where algorithms for anomalies detection are executed, in order to identify potentially dangerous situations. If the algorithms observe suspicious values, they can trigger two kinds of alarms:

- *Minor alarm*: the robot reaches the patient to verify his/her health conditions. With its cameras, the robot analyzes his/her state of consciousness and observes pain expressions on his/her face. Moreover, with a dialogue system, the patient can be cognitively stimulated. If the data gathered in this phase show a low level of interaction between the patient and the robot, a major alarm is triggered.
- *Major alarm*: if it has not already done, the robot, controlled by a remote health professional, reaches the patient. The health professional can verify the status of the patient through the robot cameras and can use its actuators to perform a physical interaction.

The second scenario refers to the execution of physical rehabilitation activities. The robot remind to the patient the scheduled exercise. It the patient is reluctant, the robot activates its persuasion mechanisms, in order to convince him/her. The robot can also ask the person to wear medical devices to monitor vital signals. During the exercises, the robot monitors the correct execution. Through computer vision algorithms available in the *Edge Layer*, it is possible to detect if the exercises are correctly executed. The patient's body joints are tracked by the robot's cameras; their coordinates are sent to the Edge Layer, where the algorithms check the correctness of the exercises. The result is sent back to the robot that, possibly, suggests correction or encourages the patient to continue. These scenarios are addressed by the project SI-ROBOTICS[2].

5. Concluding Remarks

The need for more healthcare options for ageing populations is reflected in an assessment of available technologies. Home automation for the elderly allows them to remain at home, safe, comfortable and also saving the costs and anxiety of moving to a health care facility.

This work proposed a level of unmanned supervision, based on Edge Computing and AI techniques, which can somehow govern the steps of the Clinical Pathway that the patient should follow autonomously at his home to avoid worsening of his clinical conditions and bring him to a speedy recovery. The paper shed light on formal aspects of executing process mining tasks in an Edge infrastructure, in which activity logs are collected by data coming from medical, mobile, and interactive devices, in the spirit of IoMT perspective. Further aspects focused on

[2]SI-ROBOTICS: "SocIal ROBOTICS for active and healthy ageing".

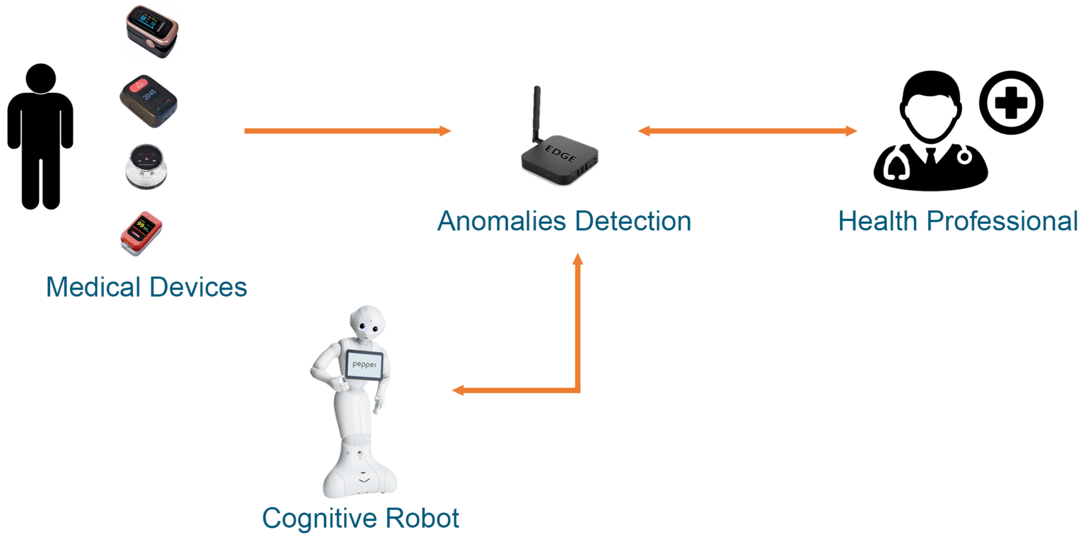

Figure 6: General flow of execution for a domiciliary hospitalization with a collaborative robot.

the logical structure of the Edge architecture and the communication protocols to be adopted in an AAL scenario. Also, three usage scenarios were described to explicate the context in which we rely.

Aware of the intrinsic vulnerability of AI techniques, we proposed also an anomaly detection module, called CPAD (Clinical Pathway Anomaly Detection). Interestingly, the detection system may act as an Explainable Security module, which allows receiving an exhaustive explanation of the attack reports that can be easily interpreted even by non Machine Learning experts and therefore in this case by the physician and the user who is undergoing treatment. In fact, the Explainability of AI, which aims to make people understand how ML models work, is essential to promote trust and reliability in AI systems. It will also allow the patient in care to have an overview of the decision-making process of the system.

Future works will be devoted to the multitude of capabilites and opportunities that the Edge module would address. Investigations will include Recommender Systems to perform a more human-understandable interaction, and Robotic Process Automation (RPA) to develop a more fine-grained integration of industrial automation. In particular, we will delve in fundamental aspects of data trustability at AI on Edge level: for instance, cognitive security will combine the strengths of AI and human intelligence. This is particular important in the healthcare domain, since it involves crucial aspects of people's life. For example, suppose that a patient is used to take a pill to control blood pressure twice a day. If some vital parameters involved in his/her pathology go out of a determined range, the Edge architecture may proactively react and change the pathway, asking the patient to take one more pill. How could the patient be serene that the modification does not depend on a malfunction? It is interesting to explore how visual explanations can improve system trustability. Nevertheless, such smart devices could have a peculiar trustability, eventually equipped with some hardware extensions. For instance, it could be beneficial to monitor some situations in which they could be hacked, unintentionally or not, by the patient. Considering the pill dispenser, by counting the number of times it is opened, it keeps track of the number of pills that the patient takes. But what does it happen if the patient picks a pill from the dispenser, but she does not actually take it because of dementia? The pill dispenser could be equipped with a micro-camera that captures arm and hand movement to check the correctness of the action. In doing so, we will be able to correct the patient's clinical path immediately. But not only, the potential of AI and robotics in the diagnostic and therapeutic field will be revolutionary both in terms of "personalization" of assistance and of diagnostic-therapeutic precision. Finally, while providing efficient and cost-effective healthcare to achieve a situation awareness, the proposed study also took a look on the quality of action that can be made by stakeholders with decision-support systems. Endowing humans with the ability to take better decision thanks to AI, and in particular AI on Edge, defines a process in which the AI can be seen as a tool capable of strengthening and increasing human skills, approaching therefore to an Augmented Intelligence.

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